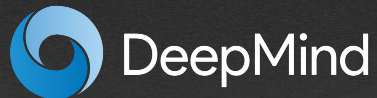


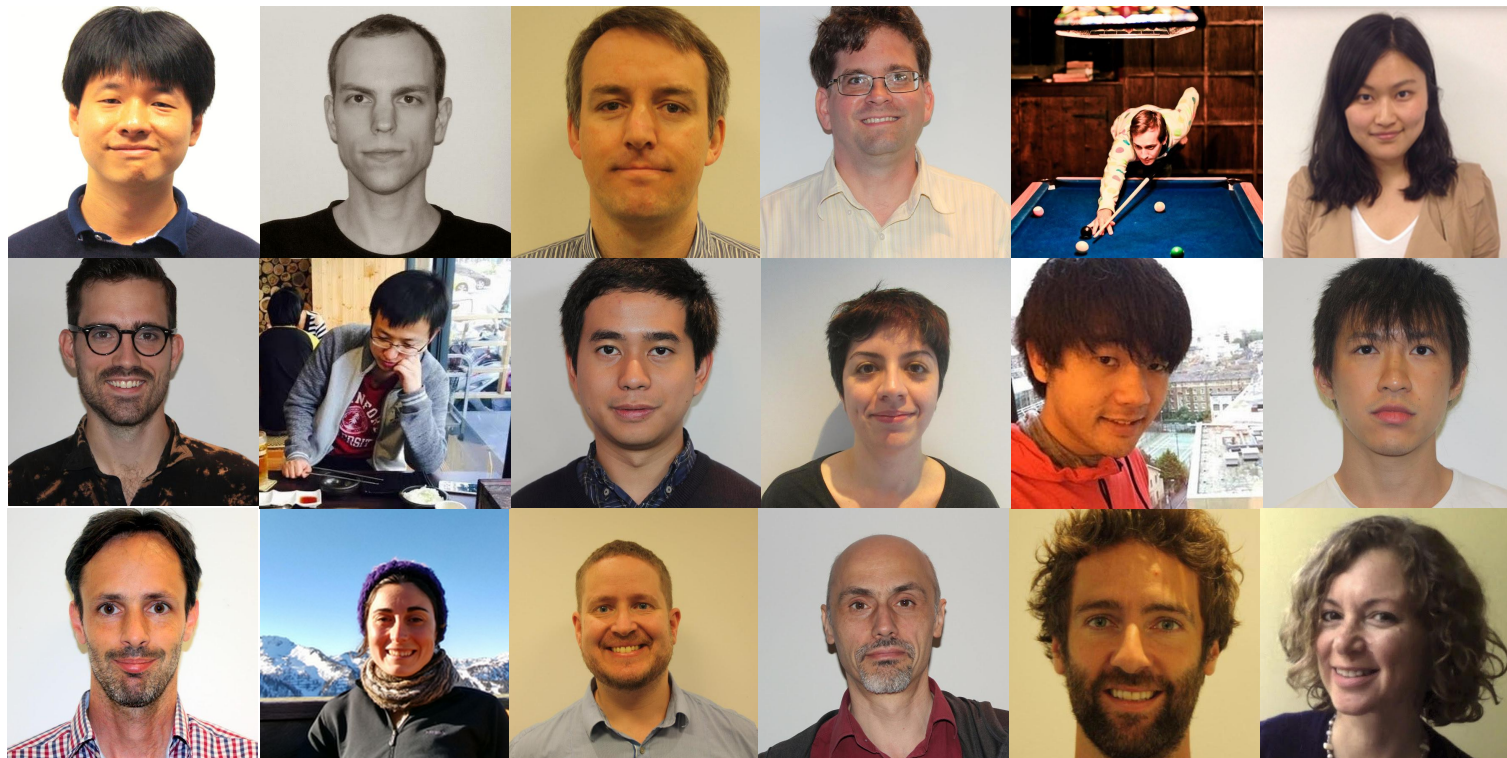
# Data Driven Reading Comprehension

**Phil Blunsom**

**In collaboration with Karl Moritz Hermann, Tomáš Kočiský, Ed Grefenstette and the  
DeepMind Natural Language Group**



# The DeepMind Language Group

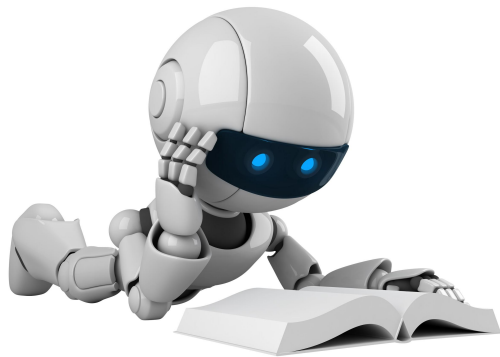


# Reading Comprehension

*We aim to build models that can read a text, represent the information contained within it, and answer questions based on this representation*

There are two broad motivations for doing this,

1. To build QA applications or products,
2. To evaluate language understanding algorithms.



# MC Test

James the Turtle was always getting in trouble. Sometimes he'd reach into the freezer and empty out all the food. Other times he'd sled on the deck and get a splinter. His aunt Jane tried as hard as she could to keep him out of trouble, but he was sneaky and got into lots of trouble behind her back. One day, James thought he would go into town and see what kind of trouble he could get into. He went to the grocery store and pulled all the pudding off the shelves and ate two jars. Then he walked to the fast food restaurant and ordered 15 bags of fries. He didn't pay, and instead headed home. ...

Where did James go after he went to the grocery store?

1. his deck
2. his freezer
3. a fast food restaurant
4. his room

# The CNN and Daily Mail datasets: aims



The screenshot shows the Daily Mail website interface. The main headline is "Why it's hell living next to the REAL interns: £4,000-a-month Googlers' ter residents at San Francisco apartment complex with their constant partying". Below this, there's a sub-headline "Google reveals it is developing a computer so smart it can program ITSELF". The article text mentions that Google interns have flooded a San Francisco Bay Area apartment complex, and the full-time residents say their partying and late hours have gotten out of control. The article is dated 18:24, 8 July 2013 and was updated at 07:55, 9 July 2013. It has 620 shares.



The screenshot shows the CNN website interface. The main headline is "Happy 75th birthday, Chuck Norris!". Below this, there's a sub-headline "Google's DeepMind artificial intelligence unit uses Daily Mail articles to teach computers how to read and understand human language". The article text mentions that British-based unit analysed almost 400,000 articles from the website used because of its unique style of bullet points, text and artificial intelligence was able to learn key facts from the news articles. The article is dated 22:36, 29 October 2014 and was updated at 00:32, 30 October 2014. It has 620 shares.

The CNN and Daily Mail websites provide paraphrase summary sentences for each full news story.

Hundreds of thousands of documents Millions of context-query pairs Hundreds of entities



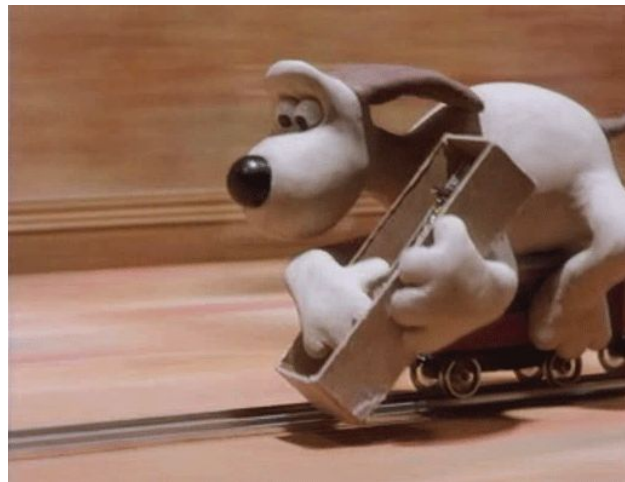
# The CNN and Daily Mail datasets: large scale RC

MC Test



500 stories, 2k questions.

CNN and Daily Mail Corpora



~300k stories and >1M questions.

# The CNN and Daily Mail datasets: the data

The BBC producer allegedly struck by Jeremy Clarkson will not press charges against the “Top Gear” host, his lawyer said Friday. Clarkson, who hosted one of the most-watched television shows in the world, was dropped by the BBC Wednesday after an internal investigation by the British broadcaster found he had subjected producer Oisin Tymon “to an unprovoked physical and verbal attack.” ...

## **Cloze-style question:**

**Query:**        Producer **X** will not press charges against Jeremy Clarkson, his lawyer says.

**Answer:**     Oisin Tymon

# The CNN and Daily Mail datasets: the data

## From the Daily Mail:

- The hi-tech bra that helps you beat breast **X**
- Could Saccharin help beat **X** ?
- Can fish oils help fight prostate **X** ?

Any n-gram language model train on the Daily Mail would correctly predict (**X** = cancer)



# The CNN and Daily Mail datasets: anonymisation

We aimed to design the task to avoid shortcuts such as QA by language modelling or correlation:

## lexicalised ...

(CNN) New Zealand are on course for a first ever World Cup title after a thrilling semifinal victory over South Africa, secured off the penultimate ball of the match.

Chasing an adjusted target of 298 in just 43 overs after a rain interrupted the match at Eden Park, Grant Elliott hit a six right at the death to confirm victory and send the Auckland crowd into raptures. It is the first time they have ever reached a world cup final.



**Question:**  
\_\_\_\_\_ reach cricket Word Cup final?

**Answer:**  
New Zealand

## ... delexicalised

(ent23) ent7 are on course for a first ever ent15 title after a thrilling semifinal victory over ent34, secured off the penultimate ball of the match.

Chasing an adjusted target of 298 in just 43 overs after a rain interrupted the match at ent12, ent17 hit a six right at the death to confirm victory and send the ent83 crowd into raptures. It is the first time they have ever reached a ent15 final.



**Question:**  
\_\_\_\_\_ reach ent3 ent15 final?

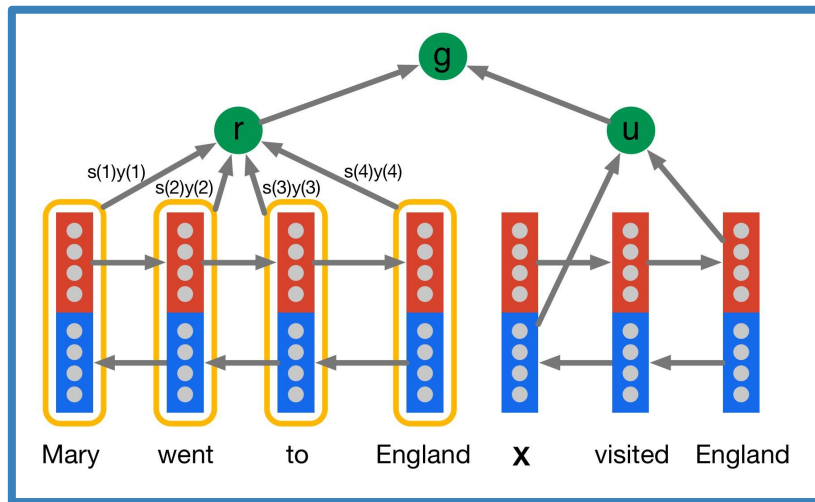
**Answer:**  
ent7

# The CNN and Daily Mail datasets: models

We proposed a simple attention based approach:

- Separate encodings for query and context tokens
- Attend over context token encodings
- Predict based on joint weighted attention and query representation

## The Attentive Reader



# The CNN and Daily Mail datasets: the good and bad

Good: we recognised that there must be a level of indirection between annotators producing questions and the text from which the questions are answered.

Bad: many of the automatically generated questions are of poor quality or ambiguous.<sup>1</sup>

<sup>1</sup>Chen et al. A Thorough Examination of the CNN/Daily Mail Reading Comprehension Task. ACL 2016

# The CNN and Daily Mail datasets: the good and bad

Good: we aimed to factor out world knowledge through entity anonymisation so models could not rely on correlations rather than understanding.

Bad: The generation process and entity anonymisation reduced the task to multiple choice and introduced additional noise.

# The CNN and Daily Mail datasets: the good and bad

Good: posing reading comprehension as a large scale conditional modelling task made it accessible to machine learning researchers, generating a great deal of subsequent research.

Bad: while this approach is reasonable for building applications, it is entirely the wrong way to develop and evaluate natural language understanding.

# Desiderata for Reading Comprehension Data sets

## Applications

If our aim is to build a product or application, we must acquire data as close to the real use case as possible, i.e. representative questions and document contexts.

If we artificially generate data we risk introducing spurious correlations, which overparameterised neural networks are excellent at exploiting.





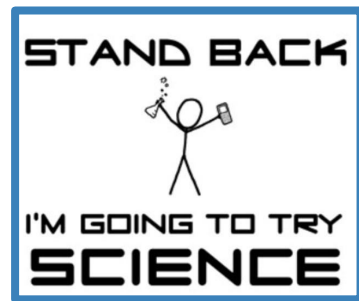
# Desiderata for Reading Comprehension Data sets

## Language Understanding

Any data annotation process will introduce spurious artifacts into the data.

Performance on a language understanding evaluation can thus be factored into two components, 1) that which measures true understanding, 2) and that which captures overfitting to the artifacts.

**If our aim is to evaluate language understanding systems we must not train on data collected with the same annotation process as our evaluation set.**



# Stanford Question Answering Dataset (SQuAD)

Question answer pairs crowdsourced on ~500 Wikipedia articles.

Answers are spans in the context passage.

In the 1960s, a series of discoveries, the most important of which was seafloor spreading, showed that the Earth's lithosphere, which includes the crust and rigid uppermost portion of the upper mantle, is separated into a number of tectonic plates that move across the plastically deforming, solid, upper mantle, which is called the asthenosphere. There is an intimate coupling between the movement of the plates on the surface and the convection of...

**Question:**

Which parts of the Earth are included in the lithosphere?

# Stanford Question Answering Dataset (SQuAD)

Good: Very scalable annotation process that can cheaply generate large numbers of questions per article.

Bad: Annotating questions directly from the context passages strongly skews the data distribution. The task then becomes reverse engineering the annotators, rather than language understanding.

## SQuAD2.0

The Stanford Question Answering Dataset

### What is SQuAD?

Stanford Question Answering Dataset (SQuAD) is a reading comprehension dataset, consisting of questions posed by crowdworkers on a set of Wikipedia articles, where the answer to every question is a segment of text, or span, from the corresponding reading passage, or the question might be unanswerable.

**New** SQuAD2.0 combines the 100,000 questions in SQuAD1.1 with over 50,000 new, unanswerable questions written adversarially by crowdworkers to look similar to answerable ones. To do well on SQuAD2.0, systems must not only answer questions when possible, but also determine when no answer is supported by the paragraph and abstain from answering. SQuAD2.0 is a challenging natural language understanding task for existing models, and we release SQuAD2.0 to the community as the successor to SQuAD1.1. We are optimistic that this new dataset will encourage the development of reading comprehension systems that know what they don't know.

[SQuAD2.0 paper \(Rajpurkar & Jia et al. '18\)](#)

[SQuAD1.0 paper \(Rajpurkar et al. '16\)](#)

### Getting Started

We've built a few resources to help you get started with the dataset.

Download a copy of the dataset (distributed under the CC BY-SA 4.0 license):

[Training Set v2.0 \(40 MB\)](#)

[Dev Set v2.0 \(4 MB\)](#)

### Leaderboard

SQuAD2.0 tests the ability of a system to not only answer reading comprehension questions, but also abstain when presented with a question that cannot be answered based on the provided paragraph. How will your system compare to humans on this task?

Rank	Model	EM	F1
	Human Performance Stanford University (Rajpurkar & Jia et al. '18)	86.831	89.452
1	VS <sup>3</sup> -NET (single model) Kangwon National University in South Korea <small>Jul 13, 2018</small>	68.438	71.282
2	KACTEIL-MRC(GFN-Net) (single model) Kangwon National University, Natural Language Processing Lab. <small>Jun 26, 2018</small>	68.224	70.871
3	KakaoNet2 (single model) Kakao NLP Team <small>Jun 26, 2018</small>	65.708	69.369
4	abcNet (single model) Fudan University & Liliushuo AI Lab <small>Jul 11, 2018</small>	65.256	69.198
5	BSAE AddText (single model) recITAL.ai <small>Jun 27, 2018</small>	63.383	67.478
5	BIDAF + Self Attention + ELMo (single model) Allen Institute for Artificial Intelligence (modified by Stanford) <small>May 31, 2018</small>	63.383	66.262
6	BIDAF + Self Attention (single model) Allen Institute for Artificial Intelligence (modified by Stanford) <small>May 31, 2018</small>	59.332	62.305
7	BIDAF-No-Answer (single model) University of Washington (modified by Stanford) <small>May 31, 2018</small>	59.174	62.093

<sup>1</sup><https://rajpurkar.github.io/SQuAD-explorer/>

# Stanford Question Answering Dataset (SQuAD)

Good: The online leaderboard allows easy benchmarking of systems and motivates competition.

Bad: Answers as spans reduces the task to multiple choice, and doesn't allow questions with answers latent in the text.

## SQuAD2.0

The Stanford Question Answering Dataset

### What is SQuAD?

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# Stanford Question Answering Dataset (SQuAD)

SQUAD provides a great resource for experimenting with machine learning models.

However, just like the CNN/DailyMail corpus, it does not satisfy the requirements for building applications, nor for evaluating language understanding systems.

## SQuAD2.0

The Stanford Question Answering Dataset

### What is SQuAD?

Stanford Question Answering Dataset (SQuAD) is a reading comprehension dataset, consisting of questions posed by crowdworkers on a set of Wikipedia articles, where the answer to every question is a segment of text, or span, from the corresponding reading passage, or the question might be unanswerable.

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# MS Marco

Questions are mined from a search engine and matched with candidate answer passages using IR techniques.

Answers are not restricted to be subspans of the documents, and some questions are not answerable from the context.

## MS MARCO V2 Leaderboard

Follow MSMarcoAI

First released at NIPS 2016 the MS MARCO dataset was an ambitious, real-world Machine Reading Comprehension Dataset. Based on feedback from the community, we designed and released the V2 dataset and its related challenges ranked by difficulty/easiness to hardest. Can your model read, comprehend, and answer questions better than humans?

1. Given a query and 10 passages provide the best answer available based on (Novice)

2. Given a query and 10 passages provide the best answer available in natural language that could be used by a smart device/digital assistant (Intermediate)

3. TBD (Expert)

Models are ranked by ROUGE-L Score

### Novice Task

Rank	Model	Submission Date	Rouge-L	Bleu-1	F1
1	Human Performance	April 23th, 2018	53.87	48.50	94.72
2	VNET Baidu NLP	June 19th, 2018	46.72	50.45	70.96
3	SNET JY Zhao	June 28th, 2018	42.36	46.14	70.96
4	DNET++ QA Geeks	June 1st, 2018	41.91	45.80	70.93
5	SNET+seq2seq Yihan Ni of the CAS Key Lab of Web Data Science and Technology, ICT, CAS	June 1st, 2018	39.82	42.27	70.96
7	DNET QA Geeks	May 29th, 2018	33.30	29.12	74.36
8	BIDAF+seq2seq Yihan Ni of the CAS Key Lab of Web Data Science and Technology, ICT, CAS	May 29th, 2018	27.60	28.84	70.96
9	BIDAF Baseline (implemented By MSMARCO Team) Allen Institute for AI & University of Washington [Seo et al. '16]	April 23th, 2018	23.95	10.64	74.93

### Intermediate Task

Rank	Model	Submission Date	Rouge-L	Bleu-1
1	Human Performance	April 23th, 2018	63.21	53.03
2	VNET Baidu NLP	July 4th, 2018	46.41	43.12
3	ConZNet ISR	June 14st, 2018	41.68	37.52
4	Bayes QA Bin Bi of Alibaba NLP	June 14st, 2018	41.11	43.54
5	SNET+seq2seq Yihan Ni of the CAS Key Lab of Web Data Science and Technology, ICT, CAS	June 1st, 2018	40.07	37.54
6	BIDAF+seq2seq Yihan Ni of the CAS Key Lab of Web Data Science and Technology, ICT, CAS	May 29th, 2018	32.22	28.33
7	DNET++ QA Geeks	June 1st, 2018	26.15	32.24
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# MS Marco

Good: The reliance on real queries creates a much more useful resource for those interested in applications.

Bad: People rarely ask interesting questions of search engines, and the use of IR techniques to collect candidate passages limits the usefulness of this dataset for evaluating language understanding.

## MS MARCO V2 Leaderboard

Follow MSMarcoAI

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1. Given a query and 10 passages provide the best answer (available based on Novice)

2. Given a query and 10 passages provide the best answer available in natural language that could be used by a smart device/digital assistant (intermediate)

3. TBOExpert

Models are ranked by ROUGE-L Score

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# MS Marco

Good: Unrestricted answers allow a greater range of questions.

Bad: How to evaluate freeform answers is an unsolved problem. Bleu is not the answer!

## MS MARCO V2 Leaderboard

Follow MSMarcoAI

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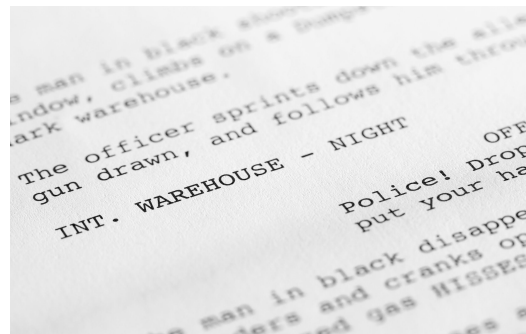
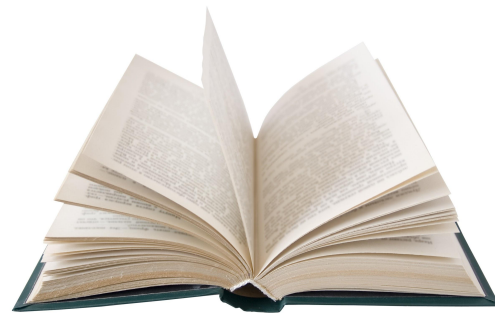
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# Narrative QA: aims

Understanding language goes beyond reading and answering literal questions on factual content.

Narratives present many interesting challenges, requiring models to represent and reason over characters and temporal relationships.

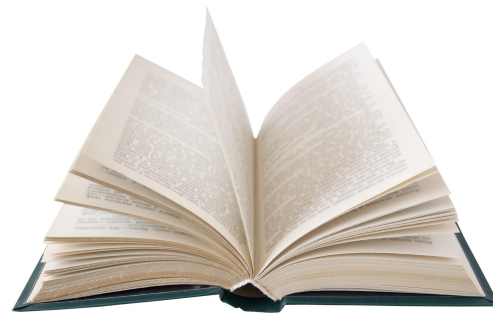


# Narrative QA: construction

Documents are **books** and **movie scripts**

Complex, long, self-contained narratives

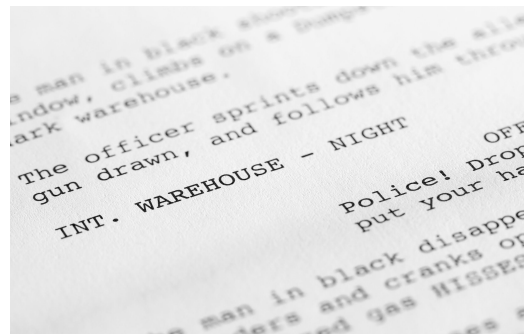
Contain dialogue



Questions from **abstractive summaries**

Summary → 30 questions with 2 answers each

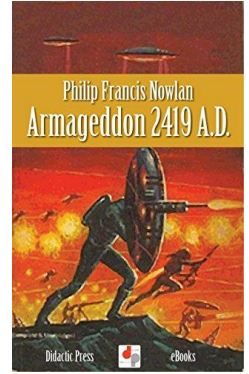
Answers are human generated



# Narrative QA: examples

**Question:** In what year did Rogers awaken from his deep slumber?

**Answer:** 2419



**Summary snippet:** ...Rogers remained in sleep for 492 years. He awakes in 2419 and...

**Story snippet:** I should state therefore, that I, Anthony Rogers, am, so far as I know, the only man alive whose normal span of eighty-one years of life has been spread over a period of 573 years. To be precise, I lived the first twenty-nine years of my life between 1898 and 1927; the other fifty-two since 2419. The gap between these two, a period of nearly five hundred years, I spent in a state of suspended animation, free from the ravages of katabolic processes, and without any apparent effect on my physical or mental faculties. When I began my long sleep, man had just begun his real conquest of the air...

# Narrative QA: examples

**Question:** How is Oscar related to Dana?

**Answer:** He is her son



**Summary snippet:** ...Peter's former girlfriend Dana Barrett has had a son, Oscar...

**Story snippet:**

*DANA (setting the wheel brakes on the buggy)* Thank you, Frank. I'll get the hang of this eventually.

She continues digging in her purse while Frank leans over the buggy and makes funny faces at the baby, OSCAR, a very cute nine-month old boy.

*FRANK (to the baby)* Hiya, Oscar. What do you say, slugger?

*FRANK (to Dana)* That's a good-looking kid you got there, Ms. Barrett.



# Narrative QA: composition

	<b>Train</b>	<b>Validation</b>	<b>Test</b>
<b># documents</b>	1,102	115	355
<b># questions</b>	32,747	3,461	10,557
<b>Avg. # tokens in summaries</b>	659	638	654
<b>Avg. # tokens in scripts</b>	29,934	29,515	29,900
<b>Avg. # tokens in books</b>	95,632	94,506	86,329
<b>Max # tokens</b>	430,061	418,265	404,641

# Narrative QA: question categories

Why doesn't Pozdnyshev run after the violinist? [**Why/reason 9.4%**]

How did Jake survive being shot? [**How/method 8.1%**]

When does Reiko realize the curse is still unbroken? [**Event 4.4%**]

What is Nora's relationship to Michael? [**Relation 1.3%**]

Person 30.5%, Description 24.5%, Location 9.7%, Entity 4.0%, Object 3.7% Numeric 3.0%, Duration 1.7%

## Narrative QA: benchmarks

We evaluated models with Bleu, Rouge, and Mean Reciprocal Rank. None of these are ideal.

Models that have performed well on tasks such as MS Marco also give similar performance when answering questions directly from the summaries.

Such models do not scale to the task of answering questions from full narratives, so we experimented with an initial IR step to retrieve candidate passages.

**All the models we tried were unable to answer a significant number of questions posed on the full narratives.**

# Narrative QA: the good and bad

Good: A challenging evaluation that tests a range of language understanding, particularly temporal aspects of narrative, and also scalability as current models cannot represent and reason over full narratives

Bad: Performing well on this task is clearly well beyond current models, both representationally and computationally. As such it will be hard for researchers to hill climb on this evaluation.

# Narrative QA: the good and bad

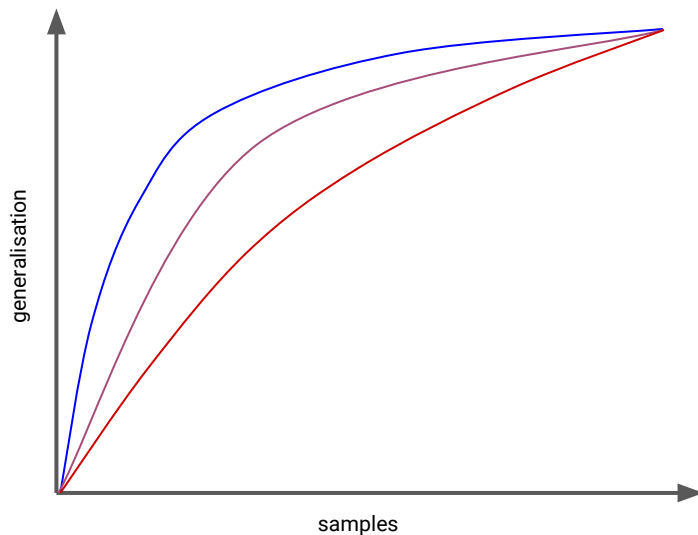
Good: The relatively small number of narratives for training models forces researchers to approach this task from a transfer learning perspective.

Bad: The relatively small number of narratives means that this dataset is not of immediate use for those wanting to build supervised models for applications.

# Transfer learning and Sample Complexity

We need to move away from training narrow supervised RC language understanding models towards a transfer learning paradigm.

This will require to us to let go of our CL obsession with single point accuracy comparisons and embrace sample complexity as the true goal.

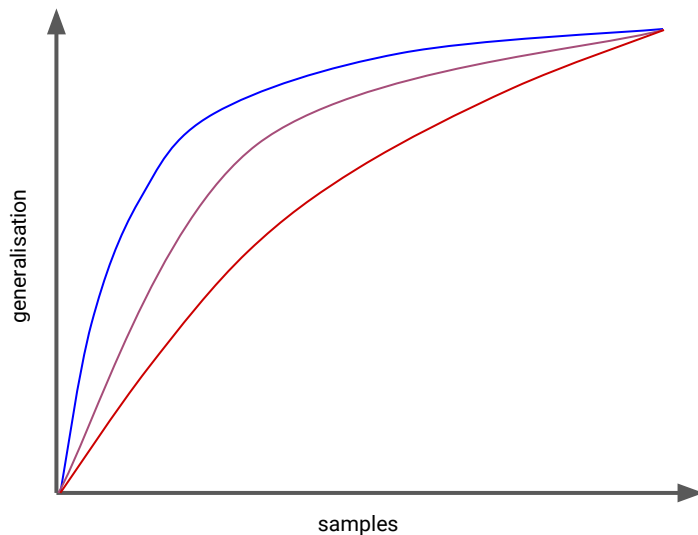




# Transfer learning and Sample Complexity

Multitask learning is not the answer.

It is easy to grow neural networks with the number of tasks, thus allowing models to overtrain to the idiosyncrasies of each task.



# Summary

The marriage of machine learning models, large data sets, and reading comprehension has produced a vibrant research environment.

We must move beyond this paradigm, embracing a variety of language and focusing on representation and inference over local context and correlation.

# Thank You.

## Data Driven Reading Comprehension

Phil Blunsom

In collaboration with Karl Moritz Hermann, Tomáš Kočiský, Ed Grefenstette and the  
DeepMind Natural Language Group

